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Machine Learning of Harmonic Relationships which Maximise Source Detection and Discrimination

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1 Extended Abstract

Typically, acoustic data received via passive sonar systems in underwater environments is transformed into the frequency domain using the Short-Time Fourier Transform. This allows for the construction of a spectrogram image in which time and frequency are the axes and intensity represents the power at a particular time and frequency. It follows from this that if a (stationary or non-stationary) periodic component is present during some consecutive time frames a track or line will be present within the spectrogram. The problem of automatic detection of these tracks drew increasing attention in the literature during the mid 1980s and research expanded during the 1990s and early 21st century. It is an ongoing area of research with contributions from a variety of backgrounds ranging from statistical modelling and image processing to expert systems. It forms a critical stage in the detection and classification of sources in passive sonar systems and the analysis of vibration data. Applications are wide ranging and include identifying and tracking marine mammals via their calls, identifying ships, torpedoes or submarines via the noise radiated by their mechanics, meteor detection and speech formant tracking.

Recently track detection algorithms have been proposed which aim to boost detection rates in low signal-to-noise ratio spectrograms by integrating information from locations in the image determined by harmonic relationships in the signal[1]. These relationships, the relative spacing between tonal harmonics and the fundamental frequency, are characteristic of the particular mechanical components within a source such as the propulsion and auxiliary machinery (engine, motors, reduction gears, generators and pumps etc.) [2]. Algorithms of this sort can be tailored to detect a particular source even in the case that harmonic relationships are not defined as integer multiples but as some arbitrary linear relationship. Currently these harmonic relationships are manually determined, either through observation, or through analysis of a source's mechanical structure. In remote sensing applications it may not be possible to have *a priori* knowledge regarding a source's mechanical components. Additionally, different operating conditions may excite or inhibit the mechanisms which produce particular harmonics and therefore the components which are observed. This complicates the manual identification of a source's characteristic harmonics. Machine learning

techniques can be applied to this problem, to determine automatically the linear relationships of harmonic components which identify the source within varying conditions. One drawback of supervised machine learning is the requirement for manually labelled ground truth data. If this is not available there are two approaches to overcoming this problem: utilising *unsupervised* learning techniques, which removes the requirement for ground truth data; or employing supervised learning techniques but using noisy, automatically generated, ground truth data. This noisy ground truth data can be generated using a detection mechanism which has a high true positive as well as a high false positive detection rate (which is a common trade-off when performing detection within noisy data). If a suitable supervised machine learning technique is applied, and enough training data is available, the relationships between true frequency components, which are common between multiple observations, will be reliably discovered.

An additional complication in the automatic discrimination of sources based upon harmonic components is that subsets of these components belonging to distinct sources may overlap. The degree to which these overlap will directly influence a system’s ability to distinguish between the sources which share common subsets. Multi-objective optimisation can be employed to minimise these effects by determining the optimal combination of components which uniquely identifies each source with respect to all other sources. Thus, optimising the system’s ability to discriminate between sources. This type of optimisation problem is ideal for supervised machine learning techniques which are able to optimise complex hypotheses. Evolutionary computing methods such as genetic algorithms are one such technique [3]. These stochastic search algorithms search a large space of hypotheses, progressively refining multiple competing hypotheses until an optimal solution is found according to a predefined fitness function. As these algorithms perform searches in large spaces the optimisation can take time. However, once the system has been designed, the optimisation is a fully automatic process which is performed off-line and only needs to be repeated when a new set of sources are to be included.

In conclusion, as far as we are aware, machine learning techniques have not been applied to the area of automatic detection and discrimination within acoustic data in underwater environments. This extended abstract has outlined two areas in which their application could improve existing systems. Namely, the automatic identification of reliable time-invariant features for remote sources and the optimisation of these features for source discrimination and detection. Issues concerning the application of these methods have also been outlined and methods to resolve them have been proposed.

References

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